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Forecasting with Leading Indicators by means of the Principal Covariate Index

by
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A new method of leading index construction is proposed, which explicitly takes into account the purpose of using the index for forecasting a coincident economic indicator. This so-called principal covariate index combines the need for compressing the information in a large number of individual leading indicator variables with the objective of forecasting. In an empirical application to forecast future growth rates of the Conference Board's Composite Coincident Index and its constituents, the forecasts of the principal covariate index are more accurate than those obtained either from the Composite Leading Index of the Conference Board or from an alternative index-based on principal components.

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1. Introduction

The construction and use of composite coincident and leading indexes to measure and forecast the state of the economy has a long tradition, starting with the work of Mitchell and Burns (1938) on business cycles. Index methods have received renewed interest over the last decade of the previous century, with important contributions by, among others, Diebold and Rudebusch (1991), Hamilton and Perez-Quintos (1996) and Stock and Watson (2002a), and the interest remains strong, see Marcellino (2006) for a recent overview. One of the developments that has led to this "revival" of index methods is the increasing availability of large data sets, consisting of up to several hundreds of economic variables. Such large data sets make the need to summarize the information by means of an index more pressing.

The construction of an index in a data-rich environment requires some kind of data compression. The so-called diffusion index method of Stock and Watson (2002a) is of special interest in this respect, as it performs relatively well in many cases. The idea of a diffusion index is to summarize the information in a set of relevant economic variables by taking a weighted average of these variables. The weights are determined in such a way that the amount of variation in the variables that is captured by the index is as large as possible. In statistical terms, the index corresponds with the (first) principal component of the set of economic variables, after appropriate scaling so that all variables have zero mean and unit variance. The Principal Component Regression (PCR) method has been used for macroeconomic forecasting in Stock and Watson (1999, 2002a, 2006), while its use within the area of monetary policy is investigated by Bernanke and Boivin (2003) and Bernanke, Boivin and Eliasz (2005), among others. The Chicago Fed National Activity Index (CFNAI) is based on the first principal component constructed from a set of macroeconomic indicators. Several extensions of the diffusion index method have been proposed, see Boivin and Ng (2005) for a forecast comparison. Index-based methods incorporate the information of a large amount of economic variables and can be seen as a pragmatic alternative to models based on economic theory that involve only a small number of variables. For recent discussions on the relative merits of economic theory and index methods in forecasting we refer to Bachmeier, Li and Liu (2007), Bachmeier and Swanson (2005), Banerjee and Marcellino (2006), Forni, Hallin, Lippi and Reichlin (2003), and Granger (2005).

In the PCR method, the index is constructed from the underlying economic variables without explicit reference to the variable that is to be predicted. That is, the index is constructed in a way that does not depend on the forecast objective, and it may well be that the (first) principal component is not the most suitable index for forecasting purposes. One possible way to incorporate the forecast objective is to select a subset of variables prior to the index construction. For example, Bai and Ng (2008) propose to select targeted predictors, that is, variables that are most closely related with the target variable, see also Bair, Hastie, Paul, and Tibshirani (2006) and Boivin and Ng (2006). In this paper we propose an alternative way to incorporate the forecast objective, namely, by constructing the index by optimizing a criterion function that takes the forecast quality of the index explicitly into account. This approach leads to a new index, the "Principal Covariate Index". This index is constructed by means of principal covariate regression (PCOVR), introduced by De Jong and Kiers (1992) in the context of static regression models and extended to a time series forecasting setting in Heij, Groenen, and Van Dijk (2006). The motivation for this index is that more accurate forecasts may be obtained by taking the specific forecasting purpose into account when constructing the index.

We assess the benefits of combining the need for data compression with the objective of forecasting in an empirical application to forecast the Composite Coincident Index (CCI) of the Conference Board. We forecast CCI growth rates over horizons ranging between one-quarter and one-year, based on diffusion index models. We first consider the construction of the index from the ten leading indicator variables that together make up the Composite Leading Index (CLI) of the Conference Board. We consider three index methods: PCR, PCOVR, and the CLI itself. The outcomes show that considerable forecast gains can be obtained by using PCOVR, that is, by tuning the index to the specific forecast task at hand. Next, we present a more extensive forecast comparison by considering wider sets of target variables, predictor variables, and prediction models. Apart from the CCI, we consider also forecasts of the four coincident indicators, that is, Industrial Production, Employment, Personal Income, and Manufacturing and Trade Sales. The set of ten leading indicators is extended to a set of 128 macroeconomic variables, and the forecast performance of the alternative index methods is compared both with and without variable selection. Further, the prediction models are extended to allow for lagged effects. The attention will be restricted to single-index models, both because the benchmark CLI is a single index and because the differences between PCR and PCOVR can be studied without the confounding effects of multiple indexes.

The paper is structured as follows. We outline the main ideas of the PCR and PCOVR methodology in Section 2, and we describe the data and forecast evaluation methods in Section 3. Sections 4 through 6 contain the empirical results. The in-sample fit and the out-of-sample forecast quality of the three index methods is compared in Sections 4 and 5. In Section 6, we compare the forecast accuracy of the three methods within a richer class of forecast models and if a larger set of 128 economic variables is used in the construction of the indexes. Section 7 concludes, and the Appendix contains a summary of the main data.

2. Index construction and forecasting

In this section, we provide a brief description of the PCR and PCOVR methods for constructing composite leading indexes and their use in forecasting a target variable. For further details of the PCR and PCOVR methods we refer to Stock and Watson (2002a, 2006) and Heij, Groenen and Van Dijk (2006), respectively.

We use the following notation. Let y_t denote the economic variable that we wish to forecast, and let h be the forecast horizon of interest. We denote the h-step ahead forecast of y_{t+h} based on information available at the end of period t by $\hat{y}_{t+h,t}$. In the empirical application that we consider here, y_t is taken to be the growth rate over the previous h months of the Conference Board's Composite Coincident Index (CCI) or one of its components, so that $\hat{y}_{t+h,t}$ is the predicted h-month growth rate in months $t+1$ through $t+h$. Let the number of leading indicator variables or predictor variables be N, and let x_{it} denote the value of the i-th predictor at time t. Two questions should be answered in order to produce a forecast of y_{t+h} by means of a composite index. The first question is how the composite index should be constructed from the individual leading indicator variables x_{it}. The second question is how the index should be related to the target variable. Marcellino (2006) provides a comprehensive overview of approaches that have been considered to resolve these issues. Many popular methods construct the composite index, denoted f_t, by taking a linear combination of the leading indicators, that is,

$$f_t = \gamma_1 x_{1t} + \gamma_2 x_{2t} + \cdots + \gamma_N x_{Nt}. \tag{1}$$

Following Stock and Watson (2002a), we refer to f_t as a diffusion index (DI), or simply as an index. The relationship between the composite index and the target variable is usually assumed to be linear, so that the forecast $\hat{y}_{T+h,T}$ is given by

$$\hat{y}_{t+h,t} = \alpha + \beta f_t. \tag{2}$$

Sometimes, $\hat{y}_{T+h,T}$ is called a composite leading index, see Marcellino (2006), but we will reserve this name for the index f_t. Both the PCR and PCOVR methods make use of a DI of the form (1) and a linear forecasting rule as in (2), but they differ crucially in the way the coefficients α, β, and γ_i, $i = 1, \dots, N$, are obtained from the data.

The PCR approach consists of two sequential steps. First, the coefficients γ_i are chosen by maximizing the variance of the index values $\{f_t\}_{t=1}^{T-h}$, under the normalization constraint that $\sum_{i=1}^{N} \gamma_i^2 = 1$, where T denotes the current forecast origin. This is motivated by the fact that in this way the maximal amount of variation present in the set of predictors x_{it}, $i = 1, \dots, N$, is retained. The solution is given by the first principal component of the N (normalized) predictor variables. Another interpretation is that the first principal component provides the best possible approximation of the set of (normalized) predictors by means of a single index, that is, it minimizes the sum of squared errors

$$\sum_{i=1}^{N} \sum_{t=1}^{T-h} (x_{it} - \delta_i f_t)^2, \tag{3}$$

where the coefficient δ_i is chosen in an optimal way by regressing the i-th predictor x_{it} on the index f_t. In the second step of PCR, the coefficients α and β are obtained by regressing y_{t+h} on the PCR index f_t, that is, by minimizing

$$\sum_{t=1}^{T-h} (y_{t+h} - \alpha - \beta f_t)^2. \tag{4}$$

Finally, the forecast $\hat{y}_{T+h,T}$ is obtained from (2), using the estimates of α and β and f_T, the index value at time T, which is constructed by means of (1) using the estimates of γ_i and the observed values of the predictors x_{iT}.

Although the purpose of the PCR index is to provide forecasts of y_{t+h}, the construction of the index f_t in the first step does not depend on this target variable. Marcellino (2006) mentions this as the main drawback of non-model based composite indexes such as the PCR index. The forecast accuracy can possibly be improved by incorporating the forecasting aim in the construction of the index. Several model-based approaches are available for this purpose, see Marcellino (2006) for discussion and Carriero and Marcellino (2007) for an empirical comparison. Here we consider an alternative approach, which retains the simplicity of non-model based composite indexes but which takes the forecasting aim explicitly into account. This Principal Covariate Regression (PCOVR) method corresponds to minimizing a single objective function, which is defined as a weighted average of the data compression objective (3) and the forecasting objective (4). That is, the coefficients α, β, γ_i, and δ_i are determined jointly by minimizing

$$w_1 \sum_{t=1}^{T-h} (y_{t+h} - \alpha - \beta f_t)^2 + w_2 \sum_{i=1}^{N} \sum_{t=1}^{T-h} (x_{it} - \delta_i f_t)^2, \tag{5}$$

with $f_t = \sum_{i=1}^{N} \gamma_i x_{it}$, and where $w_1 > 0$ and $w_2 > 0$ are weights that express the relative importance of the two objectives. In our applications, the predictors are normalized so that $\sum_{t=1}^{T-h} x_{it}^2 = 1$, and we define $w_1 = w \Big/ \sum_{t=1}^{T-h} y_{t+h}^2$ and $w_2 = (1-w) \Big/ \sum_{i=1}^{N} \sum_{t=1}^{T-h} x_{it}^2 = (1-w)/N$, where $0 < w < 1$. With this scaling, $w = 0.5$ corresponds to equal weights for the two objectives in terms of normalized variables y_t and x_{it}. If $w \to 0$ then $w_1 \to 0$, so that the PCOVR criterion (5) becomes equivalent to (3) and the PCOVR index becomes equivalent to PCR, whereas for $w \to 1$ the index will focus almost exclusively on approximating the target variable y_{t+h}.

In our applications, we choose the weight w by means of cross validation, using a small grid of weights to choose from. We use five-fold cross-validation, and the considered grid values for w are 0.01, 0.1, 0.3, 0.5, 0.7, and 0.9. For each given value of w, the data sample $1 \leq t \leq T - h$ is split into five roughly equal-sized parts. For each part (the validation sample), (5) is estimated using the data of the other four parts (the training sample), and we choose the value of w that minimizes the sum total of the squared forecast errors on the five validation samples. For this value of w, the values of $(\alpha, \beta, \gamma_i, \delta_i)$ are estimated by minimizing (5) over the sample $1 \leq t \leq T - h$, and the forecast $\hat{y}_{T+h,T}$ is constructed in the same way as in the PCR method described before.

The Conference Board's CLI can be used in a similar way for forecasting $\hat{y}_{T+h}$. If f_T denotes the value of the CLI at time t, then we may construct the forecast $\hat{y}_{T+h,T} = \alpha + \beta f_T$ using estimates of α and β that are obtained by means of a regression as in (4).

3. Data, forecasting, and evaluation

3.1. Data

In the main part of our empirical analysis, the target variable that we aim to predict is the annualized h-month growth rate of the Conference Board's CCI, defined by $y_t = (1200/h) \times \log(z_t / z_{t-h})$, where z_t is the original CCI series. In Section 6, we consider forecasting h-month growth rates of each of the four components of the CCI. The set of predictors x_{it} consists of the ten components of the Conference Board's CLI, that is, average weekly hours in manufacturing, average weekly initial claims for unemployment insurance, manufacturers' new orders for consumer goods and materials, manufacturers' new orders for nondefense capital goods, vendor performance slower deliveries diffusion index, building permits for new private housing units, the S&P 500 stock price index, M2 money supply, the spread between the 10-year Treasury bond rate and the Federal Funds rate, and the University of Michigan index of consumer expectations. We refer to the Business Cycle Indicators Handbook of the Conference Board (2001) for further background on these leading indicator variables.

Monthly data for the CCI and CLI are obtained from the Conference Board, and monthly data for the ten leading indicator variables are taken from Stock and Watson (2005). The common sample period runs from January 1959 to December 2003. We apply the same data transformations to the CLI components as in Stock and Watson (2002a, 2005) to obtain stationary variables. The CLI itself is transformed to stationarity by taking monthly growth rates. Appendix A provides further information on these data.

3.2. Recursive forecasting

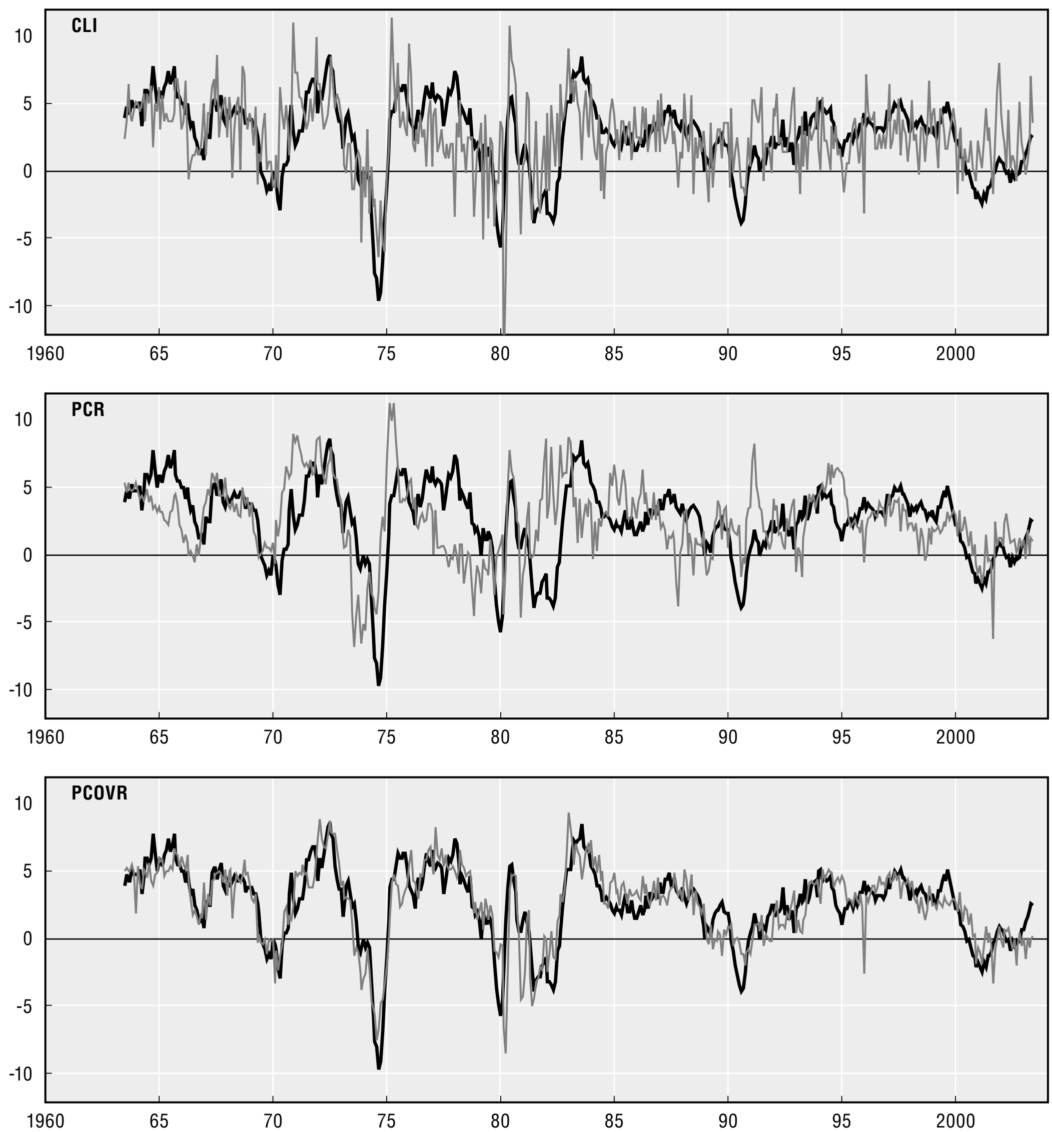
The CLI, PCR, and PCOVR methods are compared in terms of their simulated out-of-sample forecast performance. This means that, for given forecast origin T and forecast horizon h, the CLI, PCR, and PCOVR indexes are constructed as described in Section 2, providing a forecast $\hat{y}_{T+h,T}$ of the CCI growth rate over the coming h months. Note that, in computing this forecast, the used information consists of the data on the predictor variables x_{it} and the target variable y_t up to and including time T, so that the forecast is indeed out-of-sample in this sense. We consider forecast horizons h equal to 3, 6, and 12 months. As the sample period 1959-2003 may contain structural breaks, we use a moving window of ten years with 120 monthly observations to construct the index and to estimate the forecast equation. By moving the forecast origin T sequentially forward by one month at a time, we obtain a series of forecasts $\hat{y}_{T+h,T}$ and corresponding forecast errors $e_{T+h,T} = y_{T+h} - \hat{y}_{T+h,T}$. For each forecast horizon, the first forecast origin T_0 is the end of December 1969, while the final forecast is constructed for the growth rate during the h-month period ending in December 2003. Hence, the final forecast origin and the number of forecasts depend on the forecast horizon. More precisely, the last forecast origin lies h months before December 2003, as this is the last month for which the forecast can be compared with the actual h-month growth rate. The number of forecasts for horizon h is therefore equal to $n_h = 408 - h$.

The out-of-sample forecast quality of the h-month growth rate forecasts is evaluated by means of the mean squared forecast error (MSE), defined as $\frac{1}{n_h}\sum_{T=T_0}^{T_0+n_h-1} e^2_{T+h,T}$. Differences in MSE between alternative index methods are assessed by means of the Diebold-Mariano t-test with HAC standard errors, see Diebold and Mariano (1995) and Newey and West (1987).

4. Comparison of in-sample properties

Before evaluating the out-of-sample predictive accuracy of the index-based forecast methods discussed in Section 2, we first provide some insight into their in-sample characteristics. Figure 1 shows the six-month growth rate of the CCI together with the CLI, PCR, and PCOVR index series over the period from July 1963 until June 2003, which is the final forecast origin considered for six-month growth rate forecasts. The CLI is constructed directly from the index data as reported by the Conference Board, see Appendix A for details. On the other hand, the plotted PCR and PCOVR index series consist of four parts, being the index series as constructed at the forecast origins June in the years 1973, 1983, 1993, and 2003, which are based on the in-sample period covering the preceding ten years. For ease of comparison, all three index series are scaled such that they have the same mean and variance as the CCI growth rate over each of the four sub-periods. The visual evidence in Figure 1 clearly indicates that the PCOVR index follows the CCI series more closely than the other two indexes. This holds true also for the other forecast horizons of three and twelve months. These results are not shown here to save space, but are available upon request.

Figure 1. **CCI six-month growth rate (bold line) and three index series (CLI, PCR, and PCOVR, thin lines)**



Further evidence supporting the relatively better approximation of the CCI growth rate by the PCOVR index is provided in Table 1, which shows the correlations between the CCI growth rate and the three index series. More precisely, at each forecast origin T, the index series are constructed over a time window of ten years, running from month $T - 119$ till the current month T. The correlations of the PCR and PCOVR indexes with the h-month CCI growth rate in Table 1 consist of their correlation over this in-sample period of ten years, averaged over the set of all considered forecast origins. The PCOVR index has clearly the largest correlation with the CCI growth rate for all time periods and for all forecast horizons considered. This reflects the fact that the PCOVR index is tuned towards the variable to be predicted, whereas this does not hold true for the CLI and the PCR index.

Table 1. **Within-sample correlations between indexes and CCI**

Forecast period (sample size)	h	CLI	PCR	PCOVR
1970-2003	3	0.41	0.45	0.71
(408-h)	6	0.41	0.52	0.76
	12	0.41	0.56	0.78
1970-1983	3	0.49	0.33	0.73
(168)	6	0.49	0.48	0.81
	12	0.49	0.65	0.88
1984-1993	3	0.16	0.65	0.74
(120)	6	0.16	0.62	0.73
	12	0.16	0.57	0.72
1994-2003	3	0.17	0.44	0.65
(120-h)	6	0.17	0.47	0.72
	12	0.16	0.44	0.71

Notes: For CLI, the table shows the (absolute) correlation of CLI with the CCI growth rate over the indicated forecast periods. For PCR and PCOVR, the table shows average correlations, as the index series is re-estimated every month. At forecast origin T, the PCR and PCOVR indexes are estimated over a window of 120 months, corresponding to the months $T - 119 \leq t \leq T$, and the absolute value of the correlation between this series and the predicted variable over the same estimation window is computed. This correlation is averaged over all forecast origins in the considered forecast period. For example, for 1970-2003 and forecast horizon $h = 12$, the correlations are averaged over the 396 forecast origins from 1970.01 till 2002.12.

The three indexes are constructed from the same underlying set of ten leading indicator variables. Table 2 shows the correlation of each index with the individual indicators, averaged across the considered forecast origins. The importance of the variables differs among the three indexes. For instance, manufacturing hours is strongly present in the PCR index, but much less so in the CLI. The correlations with the PCR index are often larger than those with the PCOVR index. This is not surprising, as the PCR index minimizes the residuals resulting from approximating the predictor variables by the index, see (3). On the other hand, the PCOVR index takes the correlation with the predicted variable into account as well, see (5). Further, the correlations with the PCOVR index depend on the forecast horizon. The largest correlation in the short run (for $h = 3$ and 6) is obtained for Building Permits, whereas in the long run (for $h = 12$) this is obtained for the Interest Rate Spread.

Table 2. **Correlations between three indexes and ten leading indicators**

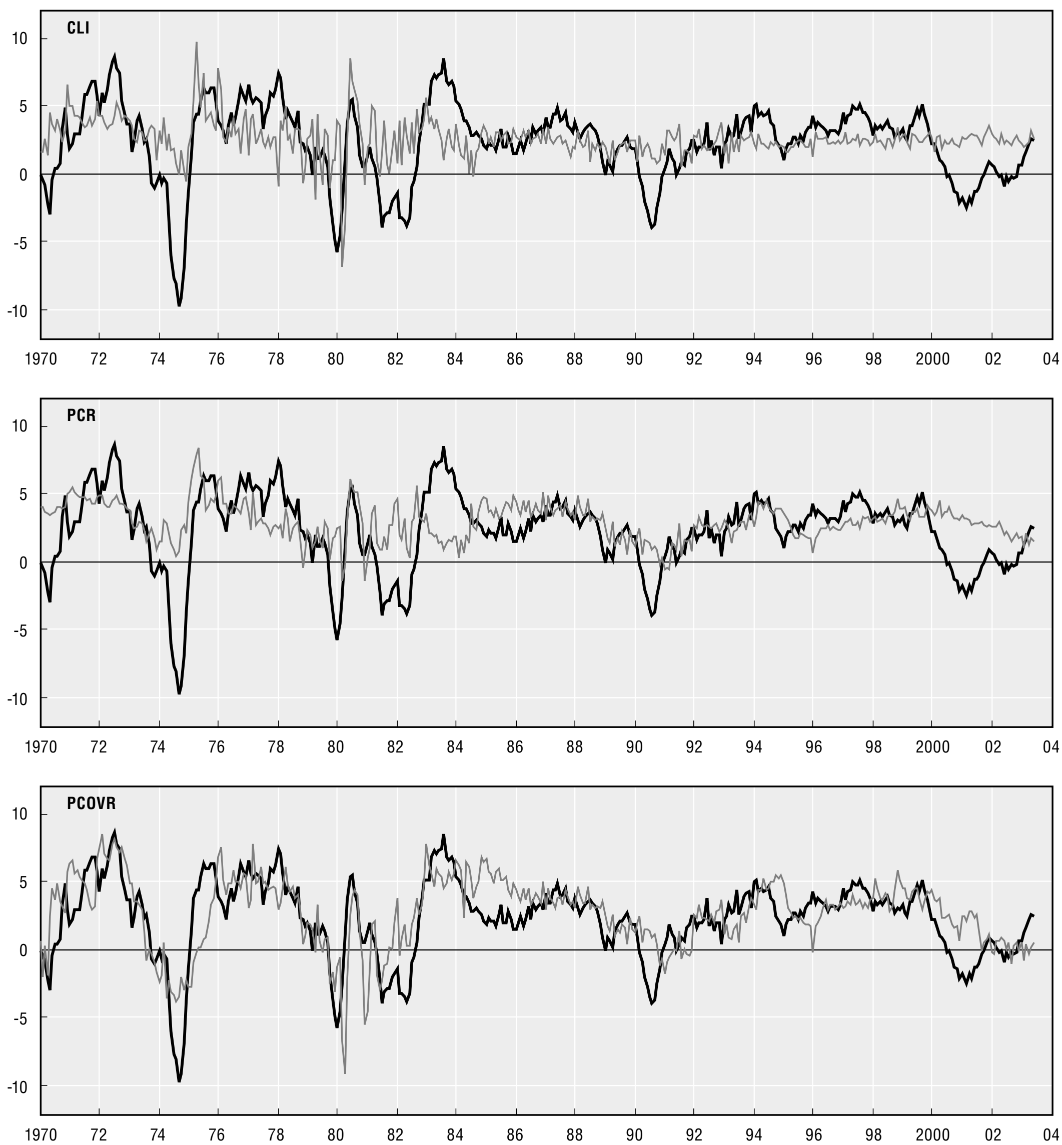
Index	h	Leading indicator									
		Hours manuf.	Unemp. claims	Orders cons.	Orders cap.	Vendor perf.	Build. permits	SP500 index	Money M2	Int. spread	Cons. expect.
CLI		0.06	0.57	0.54	0.25	0.17	0.21	0.44	0.46	0.45	0.43
PCR		0.62	0.34	0.34	0.14	0.67	0.51	0.35	0.55	0.64	0.30
PCOVR	3	0.51	0.41	0.37	0.17	0.44	0.67	0.20	0.44	0.52	0.17
	6	0.44	0.38	0.34	0.15	0.41	0.63	0.24	0.48	0.59	0.21
	12	0.37	0.33	0.30	0.12	0.47	0.52	0.26	0.53	0.67	0.23

Notes: For CLI, the table shows the (absolute) correlation of CLI with the ten leading indicators over the 405 months from 1970.01 until 2003.09. For PCR and PCOVR, the table shows average (absolute) correlations, as the index series is re-estimated every month, see Table 1. For PCR, the average is taken over the 405 months from 1970.01 until 2003.09. For PCOVR, the index depends on the forecast horizon, and the average is taken over the 408-h months from 1970.01 till 2003. (12-h)

5. Comparison of out-of-sample forecasts

We now turn to the out-of-sample predictive accuracy achieved by the three index methods. Figure 2 shows the six-month CCI growth rate together with the corresponding forecasts obtained from the CLI, PCR, and PCOVR indexes for all forecast origins from December 1969 until June 2003. The CLI- and PCR-based forecasts seem to miss many of the up- and downward movements of the CCI, whereas PCOVR follows these cycles more closely. Table 3 shows this in more detail by means of the correlations between the actual growth rates and the out-of-sample forecasts. For all forecast horizons and sub-periods considered, PCOVR provides the highest correlation, often outperforming the CLI and PCR methods by a substantial margin. For example, for the complete out-of-sample period 1970-2003, the correlation between the six-month CCI growth rate and the PCOVR forecast

Figure 2. **CCI six-month growth rate (bold line) and three index-based forecasts (CLI, PCR, and PCOVR, thin lines)**



is 0.66, as compared to 0.32 and 0.36 for the CLI and PCR forecasts, respectively. It also becomes clear from the table that the correlations tend to be the highest for all three index methods for the relatively volatile period 1970-1983. The correlations are smaller for the decade 1984-1993, while in the final sub-period 1994-2003 the CLI and PCR based forecasts often even have a negative correlation with the actual growth rate. PCOVR performs reasonably well in all periods.

Table 3. **Out-of-sample correlations between index-based forecasts and CCI**

Forecast period (sample size)	h	CLI	PCR	PCOVR
1970-2003	3	0.32	0.31	0.62
(408-h)	6	0.32	0.36	0.66
	12	0.33	0.44	0.68
1970-1983	3	0.40	0.34	0.65
(168)	6	0.42	0.45	0.71
	12	0.42	0.60	0.80
1984-1993	3	0.14	0.45	0.52
(120)	6	0.18	0.43	0.51
	12	0.26	0.51	0.51
1994-2003	3	–0.21	0.22	0.53
(120-h)	6	–0.11	0.14	0.54
	12	–0.17	–0.13	0.41

Notes: The table shows the correlation of the CCI growth rate with each index-based forecast of this growth rate over the indicated forecast periods. The forecast periods and forecast horizons h are the same as in Table 1.

The mean squared forecast error (MSE) of the three indexes is reported in Table 4. The column "var(y)" shows the variance of the actual h-month CCI growth rate, and the following four columns show the MSE relative to this variance. For comparison, the column "Const" reports the MSE that is obtained without using an index by simply taking the average growth rate over the preceding ten years as the forecast. The fact that this naive model has a (relative) MSE that is smaller than 1 in most cases shows that the mean growth rate varies over time, at least for forecast horizons longer than three months. The final three columns contain values of the t-test of equal predictive accuracy of Diebold and Mariano (1995); values in bold indicate that the method mentioned first in the header has a significantly smaller MSE than the second method, at the one-sided 5% significance level.

In the far majority of cases, PCOVR provides the most accurate forecasts and achieves the lowest (relative) MSE values. When evaluated over the full forecast period 1970-2003, the relative MSE for the PCOVR forecasts of the 6-month growth rate equals 0.50, as compared to 0.72 for both the CLI and PCR forecasts. The improvement achieved by PCOVR relative to CLI and PCR is of similar magnitude for horizons of 3 and 12 months and is approximately equal to 30%. The equal predictive accuracy test results indicate that PCOVR significantly outperforms CLI at all three horizons, and it also performs significantly better than PCR at horizons of 3 and 6 months (the difference for 12 months lies at the margin of significance).

From the results for sub-periods, we find that the gains of PCOVR are most spectacular for the relatively volatile period 1970-1983, where it performs up to twice as well as PCR for h = 12 months. For this sub-period, PCOVR has significantly smaller forecast MSE's than CLI and PCR at all three horizons. On the other hand, PCOVR does worse than CLI and PCR in the period 1984-1993, in particular for h = 12 months, although none of the losses is significant. This is the period following the Great Moderation, that is, the dramatic reduction in the volatility of many US macroeconomic variables, see Stock and Watson (2002b) and Sensier and van Dijk (2004), among others. For example, for the 6-month CCI growth rate, the variance declined by almost 80% from 14.34 during the period 1970-1983 to only 3.03 during the post-moderation period 1984-1993. Note that, especially during the first years of the period 1984-1993, the index and the corresponding forecast are constructed using 10-year observation windows that for a large part consist of data from the pre-moderation period. These data are no longer representative of the behavior of the CCI at the relevant forecast origin, which negatively affects the accuracy of the index forecasts. This explains why the simple "Constant" model performs relatively well in this period. It seems that the PCOVR index is most sensitive to the structural break in variance. This is perhaps not unexpected, as the PCOVR index depends directly on the target variable. Reassuringly, PCOVR is again consistently the best method over the last decade 1994-2003. During this final sub-period, the CLI and PCR methods do not recover and still do not provide more accurate forecasts than the "Constant" model. PCOVR performs better, although the gains in forecast power are not significant for this period.

Table 4. **Mean squared prediction errors of CCI**

Forecast period (sample size)	h	var(y)	Const	CLI	PCR	PCOVR	PCR *vs.* CLI	PCOVR *vs.* CLI	PCOVR *vs.* PCR
1970-2003	3	10.66	1.08	0.93	0.95	**0.68**	–0.53	**2.37**	**1.98**
(408-h)	6	8.17	0.86	0.72	0.72	**0.50**	–0.09	**1.94**	**1.69**
	12	5.93	0.65	0.53	0.50	**0.34**	0.53	**1.65**	1.62
1970-1983	3	19.32	1.08	0.88	0.92	**0.60**	–0.77	**2.22**	**1.88**
(168)	6	14.34	0.83	0.66	0.64	**0.40**	0.03	**2.15**	**1.75**
	12	9.79	0.60	0.47	0.39	**0.19**	1.22	**3.01**	**2.74**
1984-1993	3	4.36	1.03	1.04	**0.98**	**0.98**	0.48	0.20	–0.12
(120)	6	3.03	**0.72**	0.73	**0.72**	0.88	0.14	–0.59	–0.84
	12	2.10	0.48	0.49	**0.46**	0.88	0.37	–0.99	–1.37
1994-2003	3	4.62	1.15	1.20	1.09	**0.93**	0.15	1.35	1.48
(120-h)	6	4.00	1.03	1.03	1.03	**0.89**	–0.38	1.07	1.18
	12	3.48	0.91	0.92	1.02	**0.80**	–0.97	0.58	1.17

Notes: The column "var(y)" shows the variance of the predicted variable, the annualized h-month growth rate of the CCI. The next four columns show the MSE of each method relative to this variance; the column "Const" shows the MSE obtained by forecasting the growth rate at each forecast origin by the average over the last 10 years. MSE values in bold denote the best performing method for each period and horizon. The last three columns show Diebold-Mariano t-test values (in bold if significant at the one-sided 5% level). The forecast periods and the forecast horizons h are the same as in Table 1.

6. Results for richer data and models

Until now, we considered a relatively small set of ten leading indicator variables that is compressed in an index f_t that is used in a simple, static model $\hat{y}_{t+h,t} = \alpha + \beta f_t$ to forecast the CCI growth rate. An advantage of this approach is that it focuses on leading indicators of prime interest as we use the variables considered by the Conference Board in constructing their CLI, and that it is relatively straightforward to compute and interpret the constructed PCR and PCOVR indexes and their forecasts. In this section, we investigate the relative performance of the index methods in settings that are more complex. Specifically, we consider the use of forecast models with lagged effects and the use of more predictor variables in constructing the indexes. In addition, we consider forecasting the four CCI component series.

6.1. Dynamic models and richer data sets

Future growth perspectives may be related not only to the current values of leading indicator variables, but also to their values in the near past. This motivates the use of lagged index values in the forecast model. Further, current and past CCI growth rates may also be of importance in predicting future movements, so that it may help to include lagged values of CCI in the model. Using the notation of Section 3.1, let z_t denote the CCI series in levels, with corresponding monthly growth rate $v_t = \Delta \log(z_t)$. This is related to the predicted annualized h-month CCI growth rate y_t by means of $y_t = (1\,200/h) \times \sum_{j=0}^{h-1} v_{t-j}$. If we add q lagged index values and r lagged terms of v_t in the forecast equation, this gives

$$\hat{y}_{t+h,t} = \alpha + \sum_{j=0}^{q} \beta_{1j} f_{t-j} + \sum_{j=0}^{r} \beta_{2j} v_{t-j}.$$

Stock and Watson (1999, 2002a) call this the DI-AR-Lag model, as the forecasts are based on the diffusion index f_t and its lags and on autoregressive terms corresponding to current and lagged values of the one-month growth rate.

To apply this model, specific values for the lag orders q and r should be chosen. The results in Stock and Watson (2002a, 2006) show that the Bayes Information Criterion (BIC) works rather well in this respect, so we will follow their procedure of model selection and forecasting. We consider the set of forecast models with index lag $0 \leq q \leq 2$ and with autoregressive lag $r \leq 5$. We also incorporate models without autoregressive terms. This gives a set of $3 \times 7 = 21$ candidate models. For all three index methods, BIC is used to determine the lag orders q and r at each forecast origin T, based on a moving estimation window consisting of the past ten years of observations. For PCOVR, in addition the weights $w_1 = w / \sum_{t=1}^{T-h} y_{t+h}^2$ *and* $w_2 = (1 - w)/N$ in the criterion function (5) should be selected, that is, we should choose the weight $0 < w < 1$. We consider the same grid of values for w as before, that is, 0.01, 0.1, 0.3, 0.5, 0.7, and 0.9. For each fixed weight, the optimal lag orders are selected from the 21 candidate models by means of BIC. Finally, among the six resulting models, the optimal weight w is selected by five-fold cross validation.

As a further extension, we consider the effect of incorporating a larger set of economic variables in constructing the PCR and PCOVR indexes. As noted in the introduction, one of the main reasons for the renewed interest in index methods is the increasing availability of large data sets. The CFNAI of the Chicago Fed, for example, is based on the PCR index method applied to a set of 85 economic variables, while the macroeconomic forecasts in Stock and Watson (1999, 2002a, 2005) are based on even larger data sets of between 130 and 170 variables. Although a larger data set suggests the availability of more information, it is an open question whether this additional information can be exploited in constructing the index and, in particular, whether it leads to improved forecasting performance. The issue of data selection in index construction and business cycle modeling is discussed, among others, by Banerjee and Marcellino (2006), Boivin and Ng (2006), Dueker and Wesche (2003), Forni, Hallin, Lippi and Reichlin (2003), and Issler and Vahid (2006). Here we employ a data set of 128 variables, taken from Stock and Watson (2005). These 128 variables include the previously considered set of ten leading indicators.

We construct the PCR and PCOVR indexes either from the full set of all 128 predictors or from subsets that are selected at each forecast origin. For the selection of variables, we employ the hard and soft threshold approaches discussed in Bai and Ng (2008). In hard thresholding, the predictor x_{it} is included in the index construction only if the (absolute) t-value of the estimate of γ_i in the regression model

$$y_{t+h} = \alpha_i + \sum_{j=0}^{r} \beta_{ij} v_{t-j} + \gamma_i x_{it} + \varepsilon_{i,t+h}$$

exceeds a certain threshold. This is a time-series version of the supervised principal components method of Bair, Hastie, Paul, and Tibshirani (2006). Following Boivin and Ng (2006), we applied this selection method with the thresholds 1.28, 1.65, and 2.58 for the absolute t-value. As the qualitative performance of PCR and PCOVR is similar for all three threshold values, we discuss only the results for the threshold 1.65, corresponding to a one-sided significance level of 5%.

Hard thresholding may select highly correlated variables, as the predictive content of each variable is evaluated individually, regardless of the other variables. An alternative method is soft thresholding, which selects the variables sequentially and which evaluates the joint predictive content of sets of variables. To apply this method, the variables first have to be ranked in order of importance, and we use the method of least-angle regression (LARS) of Efron, Hastie, Johnstone, and Tibshirani (2004) for this purpose. Next, the number of selected variables is determined by minimizing BIC of regression models involving the first m of the ordered list of predictor variables (x_{1t}, x_{2t}, x_{3t}, . . .), in

$$y_{t+h} = \alpha + \sum_{j=0}^{r} \beta_j v_{t-j} + \sum_{j=1}^{m} \gamma_j x_{jt} + \varepsilon_{t+h}.$$

If the number of selected variables exceeds ten, then the predictors are first summarized by means of the ten leading principal components. This has no effect for the PCR index, as the leading principal component of the ten principal components is the same as that of the original set. However, this reduction has effect for the PCOVR index, as it prevents over fitting by reducing the number of coefficients γ_i in (5).

6.2. Results for the CCI

Table 5 reports the mean squared error of the h-month growth rate forecasts of the CCI with DI-AR-Lag models using either the CLI, PCR, or PCOVR index method. Three versions of PCR and PCOVR are considered, that is, no variable selection or soft or hard thresholding. The table has the same structure as Table 4. The column “var(y)” shows the variance of the actual CCI growth rate, and the following columns show the MSE relative to this variance. The column “AR” reports the MSE that is obtained without using an index, that is, by using only autoregressive terms in the forecast equation, which forms the natural benchmark for the DI-AR-lag models. If the MSE values of the AR model are compared with those of the “Constant” model in Table 4, it turns out that the AR model has a consistently smaller MSE, so that apparently it helps to include lagged growth rates in forecasting. Still, it is beneficial to include indexes in the forecast equation, as in the majority of cases the index-based forecasts are considerably more accurate than the AR forecasts.

For the full forecast period from 1970 till 2003, the PCOVR forecasts are most accurate on average. The forecast gains as compared to PCR are the largest in case no variables are selected. Both methods benefit from variable selection, PCR even more so than PCOVR, and hard thresholding works nearly always better than soft thresholding. For all three considered forecast horizons, the number of selected variables is about 40 on average for hard thresholding, as compared to about 10 for soft thresholding. It seems that soft thresholding eliminates too much information from the set of predictors. The results for sub-periods are similar to those obtained with simpler models in Section 5. PCOVR gains in particular in the volatile period until 1983. If variables are selected with hard thresholding, the results of PCR come close to those of PCOVR. From 1984-1993, the period after the reduction in macroeconomic volatility during the first half of the 1980s, the best results are obtained by PCR. Finally, CLI performs best in the final period 1994-2003. This indicates that index-based forecasts may be somewhat less useful in periods with moderate variations in growth rates, as it seems to pay to keep models as simple as possible in such periods.

It is also of interest to compare the results for the more complex, dynamic models based on large sets of predictor variables in Table 5 with those for the simple, static model based on ten leading indicators in Table 4. For the full forecast period 1970-2003, the forecasts of the simple models often outperform those of the dynamic models, especially for a one-year horizon. This provides an indication that it may pay to employ relatively simple models in long-term forecasting.

Table 6 provides information of the significance of the differences in forecast quality as measured by the MSE's of Table 5. As hard thresholding works better than soft thresholding, the results for the soft threshold approach are not presented. Significant gains of PCOVR as compared to PCR and CLI are obtained for the full forecast period, which is mostly due to forecast gains in the period 1970-1983. CLI performs significantly better than PCR during the period 1994-2003. Further, variable selection pays most during the volatile period 1970-1983, and especially for PCR.

Table 5. **Mean squared prediction errors of DI-AR-Lag forecasts of CCI based on 128 predictor variables**

Forecast period (sample size)	h	var(y)	AR	CLI	PCR			PCOVR		
					No	Soft	Hard	No	Soft	Hard
1970-2003	3	10.66	0.80	0.71	0.67	0.62	**0.58**	0.61	0.60	0.59
(408-h)	6	8.17	0.91	0.65	0.78	0.75	0.57	0.61	0.64	**0.53**
	12	5.93	0.98	0.76	0.96	0.66	0.61	0.67	0.69	**0.55**
1970-1983	3	19.32	0.81	0.69	0.66	0.56	0.54	0.58	**0.52**	0.55
(168-h)	6	14.34	0.96	0.63	0.80	0.69	0.49	0.55	0.51	**0.44**
	12	9.79	1.03	0.74	1.02	0.54	0.46	0.53	0.50	**0.37**
1984-1993	3	4.36	0.93	0.86	**0.72**	0.87	0.76	0.82	0.91	0.84
(120-h)	6	3.03	0.92	0.93	**0.77**	0.98	0.78	0.98	1.15	0.88
	12	2.10	0.85	0.94	**0.73**	0.92	1.04	1.42	1.33	1.18
1994-2003	3	4.62	0.65	0.65	0.65	0.74	0.67	**0.57**	0.76	0.64
(120-h)	6	4.00	0.61	**0.58**	0.70	0.87	0.83	0.63	0.92	0.73
	12	3.48	0.81	**0.74**	0.85	1.04	0.98	0.82	1.12	0.93

Notes: The table shows the mean squared prediction errors of DI-AR-Lag forecasts of the CCI growth rate. The table has the same structure as Table 4, where no lagged indexes and no AR terms are used in the forecast model. Three versions of PCR and PCOVR are considered, depending on the applied variable selection technique: no selection ("No"), selection with a soft threshold ("Soft"), and selection with a hard threshold of 1.65 ("Hard").

6.3. Forecasting the four coincident indicator variables

The composite coincident index is based on four indicators, that is, production, employment, income, and sales. As these four variables are of interest themselves, we investigate whether the leading index methods are useful for forecasting the growth rates of these component series. We employ the same strategy as for CCI in the foregoing section, with dynamic forecast models and with a set of 128 predictor variables with the

Table 6. **Diebold-Mariano *t*-values for the results in Table 5**

Forecast period	h	No selection			Hard threshold			PCR Hard *vs.* No	PCOVR Hard *vs.* No
		PCR *vs.* CLI	PCOVR *vs.* CLI	PCOVR *vs.* PCR	PCR *vs.* CLI	PCOVR *vs.* CLI	PCOVR *vs.* PCR		
1970-2003	3	0.59	1.25	1.32	1.61	**1.68**	–0.20	1.61	0.27
	6	–1.29	0.65	**1.87**	1.21	**2.04**	1.00	**1.93**	1.39
	12	–1.25	0.70	1.33	1.22	1.38	1.11	1.62	1.56
1970-1983	3	0.38	1.11	1.40	1.56	**1.72**	–0.08	**1.83**	0.51
	6	–1.37	0.92	**2.29**	**1.73**	**3.22**	1.00	**2.42**	**1.69**
	12	–1.37	**1.78**	**2.09**	**2.04**	**2.34**	**1.68**	**2.32**	**2.01**
1984-1993	3	0.90	0.27	–1.47	0.80	0.15	–1.05	–0.44	–0.26
	6	1.25	–0.22	–1.20	1.09	0.27	–0.74	–0.31	0.87
	12	1.64	–0.90	–1.24	–0.37	–0.58	–0.83	–1.00	1.43
1994-2003	3	0.00	0.80	1.22	–0.20	0.16	0.60	–0.39	–0.94
	6	**–1.77**	–0.56	0.84	**–1.84**	–0.86	1.02	–1.22	–0.67
	12	**–1.72**	–0.58	0.31	**–2.78**	–1.12	0.31	–1.58	–0.47

Notes: The table shows the *t*-values of Diebold-Mariano tests for the null hypothesis of equal performance against the one-sided alternative that, for "A vs B", method A has smaller MSE than method B. The tests are based on the methods of Table 5, with DI-AR-Lag forecast models and a set of 128 predictor variables. Test outcomes that are significant at the one-sided 5% level are indicated in bold.

option to select variables by means of soft or hard thresholding. The results for soft thresholding will not be discussed, as hard thresholding works better in almost all cases. The number of variables selected by hard thresholding does not depend much on the forecast horizon and ranges from an average of 43 variables for sales to 55 variables for income. This means that between one-half and two-third of the variables are removed before constructing the PCR and PCOVR indexes.

The resulting mean squared forecast errors, expressed relative to the variance of the forecast target variable, are reported in Table 7. When evaluated over the complete forecast period 1970-2003 and including the full set of predictor variables, PCOVR often renders the most accurate forecasts. Variable selection improves the forecast quality, especially for longer forecast horizons. As expected, the improvement is larger for PCR than for PCOVR, because PCR without variable selection ignores the target variable completely, whereas PCOVR takes the forecast target into account in constructing the index. Even with selected variables, PCOVR often still provides more accurate forecasts than PCR, although the difference in their performance is no longer significant. The most considerable forecast gains as compared to CLI are again obtained for the period 1970-1983, most notably so for forecasts of employment and sales by means of PCOVR with hard thresholding.

The four coincident indicators differ considerably in terms of their relative fluctuations over the three sub-periods. For example, the variance of the growth rate of six-month sales for the period 1970-1983 is a factor 5 larger than that for the period 1994-2003, whereas this factor is only 1.7 for six-month income growth rates. Of the four considered target variables, income has the most stable variance in growth rates, and this may explain why PCR and PCOVR outperform CLI consistently in all three sub-periods. Production and sales have the least stable variance in growth rates, and the forecast gains of PCR and PCOVR for these two variables are mostly realized in initial periods. For production, PCOVR with hard thresholding also works well again in the final sub-period. For employment, PCOVR and PCR improve considerably on CLI in the initial period, especially for longer horizons, but simple AR forecasts can not be beaten in the relatively very stable period from 1984 onwards.

Table 7. **Forecast results for four coincident indicators**

Period	h	var(y)	AR	CLI	PCR		PCOVR		No PCOVR *vs.* PCR	Hard PCOVR *vs.* PCR
					No	Hard	No	Hard		
Production										
1970-2003	3	43.45	0.90	0.72	0.75	0.69	0.74	0.69	0.23	–0.07
	6	31.11	1.04	0.79	0.85	0.63	0.83	0.66	0.27	–0.57
	12	20.41	1.09	0.77	1.04	0.58	0.73	0.51	1.15	0.98
1970-1983	3	81.00	0.87	0.67	0.70	0.62	0.71	0.64	–0.07	–0.20
	6	57.36	1.00	0.71	0.82	**0.50**	0.74	0.57	0.68	–1.04
	12	36.02	1.10	0.68	1.05	**0.39**	0.58	**0.33**	1.52	0.86
1984-1993	3	14.64	1.10	0.85	1.08	1.08	1.11	1.11	–0.30	–0.21
	6	9.69	1.12	1.10	1.10	1.32	1.52	1.40	–1.37	–0.43
	12	5.89	0.91	0.95	0.91	1.24	1.55	1.38	–0.95	–0.79
1994-2003	3	18.65	0.99	0.92	0.81	0.78	**0.61**	0.69	1.35	1.40
	6	14.68	1.18	1.03	0.92	0.92	0.88	0.72	0.27	1.13
	12	12.06	1.16	1.09	1.07	1.11	1.02	0.93	0.40	0.97
Employment										
1970-2003	3	7.03	0.55	0.40	0.42	0.40	0.36	0.39	**1.81**	0.48
	6	6.08	0.66	0.51	0.54	0.50	0.47	**0.41**	**1.80**	1.40
	12	4.77	0.81	0.69	0.71	0.54	0.55	0.47	1.15	1.05
1970-1983	3	12.31	0.65	0.45	0.46	0.43	0.38	0.41	**2.11**	0.33
	6	10.32	0.79	0.59	0.61	0.53	0.49	**0.41**	**2.49**	1.62
	12	7.52	0.98	0.79	0.82	**0.50**	**0.47**	**0.39**	**2.55**	1.33
1984-1993	3	3.02	0.30	0.28	0.34	0.42	0.37	0.37	–0.72	1.27
	6	2.72	0.38	0.35	0.44	0.48	0.49	0.50	–0.46	–0.38
	12	2.38	0.55	0.59	0.57	0.83	1.01	0.82	–1.37	0.09
1994-2003	3	3.43	0.26	0.25	0.26	0.27	0.27	0.29	–0.42	–0.74
	6	3.22	0.32	0.31	0.33	0.37	0.35	0.39	–0.65	–0.31
	12	2.91	0.42	0.41	0.49	0.47	0.53	0.53	–0.19	–1.35
Income										
1970-2003	3	13.43	1.01	0.94	**0.80**	**0.77**	0.81	**0.80**	–0.17	–0.48
	6	9.05	1.17	0.99	0.93	**0.85**	0.94	**0.77**	–0.05	0.71
	12	6.23	1.19	0.96	1.05	0.90	0.97	0.89	0.52	0.13
1970-1983	3	19.62	0.99	0.89	0.82	0.78	0.84	0.84	–0.23	–0.65
	6	12.71	1.23	0.92	1.01	0.88	0.91	0.71	0.38	0.97
	12	8.66	1.16	0.81	1.14	0.90	0.95	0.82	0.71	0.57
1984-1993	3	7.99	1.10	1.08	**0.74**	**0.73**	**0.78**	**0.74**	–0.89	–0.43
	6	5.45	1.16	1.14	**0.82**	**0.83**	0.90	**0.83**	–1.02	0.01
	12	3.11	1.19	1.16	0.91	0.94	1.04	1.07	–0.92	–0.75
1994-2003	3	9.91	1.02	1.00	**0.81**	**0.79**	**0.77**	**0.74**	0.42	1.08
	6	7.29	1.05	1.08	0.84	0.80	1.05	0.89	–1.00	–0.57
	12	5.73	1.31	1.23	0.98	0.91	1.00	0.96	–0.13	–0.48
Sales										
1970-2003	3	46.70	1.04	0.91	0.96	0.88	0.88	0.85	0.97	0.61
	6	27.98	1.11	0.95	1.05	0.87	0.81	**0.78**	1.39	1.13
	12	16.71	1.12	0.88	1.08	0.79	0.69	**0.57**	1.39	1.41
1970-1983	3	82.51	1.03	0.87	0.92	0.80	0.81	0.74	1.01	0.92
	6	52.34	1.13	0.89	1.03	0.78	0.66	**0.61**	**1.82**	**2.10**
	12	32.19	1.15	0.82	1.09	0.71	0.55	**0.41**	**1.85**	**1.88**

Table 7. **Forecast results for four coincident indicators** (*cont.*)

Period	*h*	var(y)	AR	CLI	PCR		PCOVR		No PCOVR *vs.* PCR	Hard PCOVR *vs.* PCR
					No	Hard	No	Hard		
1984-1993	3	22.02	1.04	0.97	1.08	1.08	1.02	1.17	0.52	–1.12
	6	10.63	0.99	1.20	1.09	1.07	1.34	1.38	–1.55	**–1.87**
	12	5.47	0.90	1.14	0.89	**0.78**	1.37	1.07	–1.03	–1.23
1994-2003	3	20.48	1.06	1.08	1.06	1.13	1.14	1.16	–1.64	–0.48
	6	10.30	1.10	1.09	1.11	1.31	1.31	1.45	**–2.35**	–0.82
	12	5.11	1.17	1.12	1.16	1.58	1.22	1.57	–0.18	0.08

Notes: The table shows the results of DI-AR-Lag forecasts based on 128 predictor variables. The table has a structure that is similar to that of Table 5 (for the relative MSE's of AR, CLI, PCR and PCOVR) and Table 6 (for the last two columns, which show the *t*-values of Diebold-Mariano tests for the null hypothesis of equal performance against the alternative that PCOVR has a smaller MSE than PCR). MSE values in bold are significantly smaller than the corresponding MSE of CLI, and *t*-values in bold are significant at the one-sided 5% level.

7. Conclusion

We compared three methods for constructing a composite index of leading indicators to summarize the information that is present in a large set of variables. Two of these methods, the Composite Leading Index (CLI) of the Conference Board and the Principal Component Regression (PCR) index that is used by the Chicago Fed as its National Activity Index (CFNAI), select the index weights independent from the variable that is to be predicted and independent from the forecast horizon. As an alternative, we proposed the Principal Covariate (PCOVR) index that combines the objectives of index construction and forecasting. If one employs straightforward, static forecast models, the PCOVR index provides considerably more accurate forecasts of the growth rates of the Composite Coincident Index (CCI) of the Conference Board, which may be of interest for many decision makers, including bankers, investors, governments, producers, and consumers. If more complex models and data sets are applied, including lagged effects and selection of predictor variables, then PCOVR still remains to be the best performing method for CCI forecasts, especially in volatile periods. In quite many cases, the simple forecasts from static models based on twelve leading indicators outperform those generated by dynamic models based on larger sets of macroeconomic variables. PCOVR is also the best performing index method to forecast Manufacturing and Trade Sales and Employment during volatile periods, although PCR also performs well for this last variable if targeted predictors are selected prior to the factor extraction. In general, PCR benefits more from variable selection than PCOVR.

We conclude by mentioning some issues that are of interest for future research. One is the use of real-time data, as opposed to revised data that are available only after a time delay. This issue has recently received much interest, see, for instance, Chauvet and Piger (2007) and McGuckin, Ozyildirim and Zarnowitz (2007). Other studies indicate that the forecast results obtained for real-time data do not seem to differ much from those for revised data, see Bernanke and Boivin (2003). A second issue is to employ multi-factor models instead of the single-factor models studied here. Third, as pointed out by one of the referees, the alternative index methods could be compared in terms of their ability to predict business cycle turning points, for which they originally were invented. Finally, it is of interest to study the effect of structural breaks and the choice of the data period used to estimate the forecast model, see Banerjee, Marcellino and Masten (2008) and Pesaran and Timmermann (2007).

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APPENDIX: DATA

Most of the data are taken from Stock and Watson (2005). This database contains monthly observations on a set of 132 economic variables from January 1959 to December 2003, giving 540 observations on each variable. We exclude four of these variables, corresponding to regional housing starts that have missing observations. The remaining 128 variables are used as predictors in Section 6, and we refer to Stock and Watson (2005) for details on these variables. In the rest of the paper, we focus on a set of ten leading indicator predictor variables that we describe in some more detail. Further, we use the Conference Board's Composite Coincident Indicator (CCI), transformed in a way that is compatible with that of the other variables. This indicator is based on a set of four coincident indicators, each of which is also predicted in Section 6.

The table provides the names and codes of the variables in Stock and Watson (2005) and in the Business Cycle Indicators Handbook of the Conference Board (2001). The ten leading and four coincident indicators are all taken directly from Stock and Watson (2005), and the CCI and CLI are taken from the Conference Board. The table shows also the applied data transformation (column "TRF"), with the following acronyms: "lv" for "leave as is" (take the variable in levels and apply no data transformation), "Δlv" for "take first difference", "ln" for "take natural logarithm", and "Δln" for "take first difference of natural logarithm" (corresponding to the monthly growth rate).

Table A. **Coincident and leading indicators**

Name	SW Code	CB Code	TRF
Coincident indicators			
Employees on nonagricultural payrolls	ces002	BCI-41	Δln
Personal income less transfer payments	a0m051	BCI-51	Δln
Industrial production index	ips10	BCI-47	Δln
Manufacturing and trade sales	a0m057	BCI-57	Δln
Leading indicators			
Average weekly hours (manufacturing)	a0m001	BCI-01	lv
Average weekly initial claims for unemployment insurance	a0m005	BCI-05	Δln
Manufacturers' new orders (consumer goods and materials)	a0m008	BCI-08	Δln
Manufacturers' new orders (nondefense capital goods)	a0m027	BCI-27	Δln
Vendor performance (slower deliveries diffusion index)	pmdel	BCI-32	lv
Building permits (new private housing units)	hsbr	BCI-29	ln
Stock prices (500 common stocks)	fspcom	BCI-19	Δln
Money Supply (M2)	fm2dq	BCI-106	Δln
Interest rate spread (10Y T-Bonds less Federal Funds)	sfygt10	BCI-129	lv
Index of consumer expectations (University of Michigan)	hhsntn	BCI-83	Δlv

Notes: The table shows the name and codes of four coincident indicators and ten leading indicators as used by the Conference Board and in the paper of Stock and Watson (2005). The column "TRF" indicates the transformation that is applied to obtain stationary variables.